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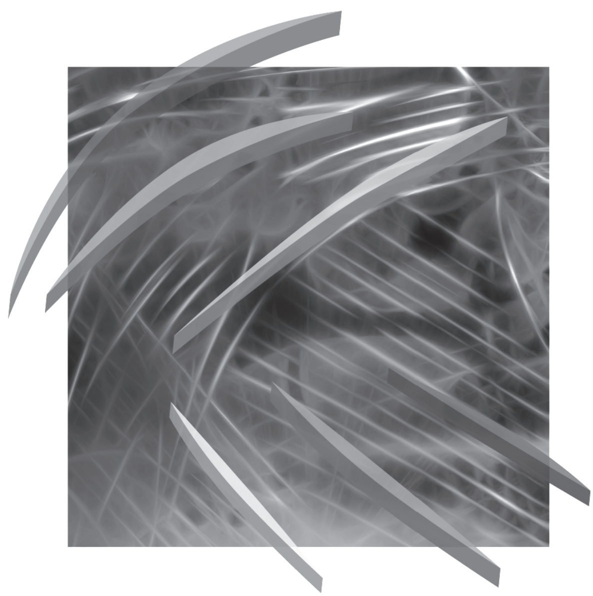

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Redakcja wydawnicza: Elżbieta Macauley, Joanna Świrska-Korłub
Redakcja techniczna: Barbara Łopusiewicz
Korekta: Barbara Cibis
Łamanie: Małgorzata Myszkowska
Projekt okładki: Beata Dębska

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Maria Mach-Król
Uniwersytet Ekonomiczny w Katowicach
e-mail: maria.mach-krol@ue.katowice.pl

ON ASSESSING AN ORGANIZATION'S PREPAREDNESS TO ADOPT AND MAKE USE OF BIG DATA

JAK OCENIAĆ GOTOWOŚĆ ORGANIZACJI DO WYKORZYSTANIA *BIG DATA*

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Summary: In the paper it is proposed to enrich the Big Data Temporal Maturity Model with a self-assessment form, based on Likert's scale. The issues of an organization's maturity in the Big Data context are presented, the Big Data Temporal Maturity Model (BDTMM) is briefly outlined, and the self-assessment form is presented and discussed. The main aim of this paper is to introduce a Big Data Temporal Maturity Model, and to present an assessment form accompanying the model. Both the model and the form have been elaborated by the author of the paper. The assessment form is based on the well-known Likert scale, and thus enables the interested organizations to check at which point of the route leading to the full use of Big Data they are now, and what they can do to progress.

Keywords: maturity model, Big Data, self-assessment, Likert's scale.

Streszczenie: W artykule zaproponowano poszerzenie modelu dojrzałości organizacji do *Big Data* o formularz samooceny organizacji, opierający się na skali Likerta. Przedstawiono problematykę dojrzałości organizacji w kontekście *Big Data*, pokazano temporalny model dojrzałości BDTMM do *Big Data* oraz przedstawiono formularz samooceny. Główne cele artykułu to prezentacja autorskiego modelu dojrzałości i wskazanie, czym różni się on od modeli istniejących, oraz prezentacja również autorskiego formularza samooceny dojrzałości, pozwalającego organizacji ocenić, na którym poziomie modelu BDTMM się znajduje.

Słowa kluczowe: model dojrzałości, *Big Data*, samoocena, skala Likerta.

1. Introduction

The shortest definition of maturity says that it is ”a state of being complete, perfect or ready” [Lahrmann et al. 2010]. A broader one is given by [Kania 2013], where the author points out that maturity arises gradually as a result of a process of shaping the needed features, enabling the performance of certain tasks. Therefore maturity is a state that may be graduated, from extreme immaturity to extreme maturity. In order to measure and assess maturity, many so-called maturity models – concerning different phenomena – have been elaborated in various domains.

Formally speaking, a maturity model is a means of identifying strong and weak points of a certain domain, and is used to assess an organization (or its part), and to delineate its development path [Lahrmann et al. 2010; Rajterič 2010].

Most commonly, maturity models come from a well-known and appreciated CMM model established in 1991 for a software development process. It was then followed by a CMMI model for assessing process maturity. In the latter model – as well as in many of its followers from different domains – a phenomenon is assessed on one of the (most common) five maturity levels.

The main aim of using maturity models is to codify knowledge on good processes/activities, on their assessment criteria, and to elaborate a systematized way of assessing a domain (see also [Mircea (ed.) 2012]).

Maturity models may be in general divided into the following categories [Kania 2013]:

- descriptive – used to determine an organization's level of maturity,
- prescriptive – describing the desired state and assessing an organization's distance to it,
- transitive – determining the steps that an organization must follow to reach the desired state.

As already pointed out, maturity models were first elaborated for process management and software development, but their usefulness and elasticity made them popular also in other domains. Also in the Big Data domain a maturity model may be a means of assessing an organization's capability to adopt this new phenomenon.

The main aim of this paper is to introduce a Big Data Temporal Maturity Model, and to present an assessment form accompanying the model. Both the model and the form have been elaborated by the author of the paper. The assessment form is based on the well-known Likert scale, and thus enables interested organizations to check at which point of the route leading to the full use of Big Data they are now, and what they can do to progress.

The paper is organized as follows: section 2 is devoted to the author's Big Data Temporal Maturity Model, in Section 3 the proposed assessment form is presented and discussed, the last Section contains the summary, conclusions and future research directions.

2. The framework of the Big Data Temporal Maturity Model

The proposed Big Data Temporal Maturity Model (BDTMM) is a means for assessing an organization's readiness to fully profit from Big Data analysis. It allows to measure the current state of an organization's Big Data assets and analytical tools, and to plan their future development. Moreover, the model explicitly incorporates the time dimension, providing a complete means also for assessing the readiness to process temporal data and/or knowledge that can be found in modern sources such as Big Data ones.

The model is composed of five maturity levels, called subsequently Atemporal, Pre-Temporal, Partly Temporal, Predominantly Temporal, and Temporal. At each level, maturity is assessed against three key aspects: data/knowledge being processed, implemented IT solutions, and functionalities provided by these solutions. Such three-tier perspective allows to examine the most important factors influencing the Big Data readability of organization. The maturity levels are numbered beginning with 0 because we start from the situation when an organization makes no use of Big Data nor of temporal data/knowledge. The description of the maturity levels is as follows.

Level 0 (Atemporal): at this level, an organization makes use only of atemporal data/knowledge, such as multidimensional data, and static knowledge. Obviously in the multidimensional data model (OLAP data) there is a time dimension, but temporal reasoning against this data is not possible. Also, at this level, an organization makes no use of Big Data nor its elements. The IT solutions implemented at this level encompass e.g. data warehouse, Business Intelligence system, and knowledge base system, which provide the following functionalities: performance monitoring, trend analysis, reporting, comparative analysis, benchmarking, and finally decision support with the use of static rules. Data warehouses and BI systems may not be considered temporal because of up till now the questions of e.g. processes representation, persistence representation, temporal operators in queries, and temporal relations analysis. The same applies to trend analysis. Although time series are time-stamped, they do not allow for temporal reasoning, they only record data in predefined time intervals.

Level 1 (Pre-Temporal): as for data/knowledge, an organization at this level uses the same structures as at the previous one, but begins also to use some unstructured data sources (like texts). The knowledge is now static or sequential. To process the data/knowledge sources, organizations implement – apart from the solutions used on level 0 – also for example intelligent dashboards and sequential knowledge base systems. Thanks to these, the following functionalities are available: predictive analytics, advanced statistics, data mining on structured data, and text mining. It is also possible to order knowledge chunks in a qualitative manner using relations such as "earlier" or "later".

Level 2 (Partly Temporal): data/knowledge at this maturity level consists of sequences, including time-stamped sequences, time-stamped knowledge. These may partially come from Big Data sources. To analyze this data/knowledge, an organization implements business optimization software, time-stamped knowledge systems, and data mining systems. Thus the following functionalities are possible: embedded analytics, optimization, and scheduling, pattern analysis, advanced data mining functions, temporal descriptive reasoning rules enabling the description of knowledge in the system and knowledge sources evolution.

Level 3 (Predominantly Temporal): an organization begins to use new Big Data sources such as sensor data and click stream data. It also collects and uses unstructured knowledge, e.g. legal regulations. To process such data and knowledge, organizations use Hadoop (and probably other Big Data tools), partly temporal knowledge base systems – that is KB systems where only the structured knowledge is temporal, while an unstructured one is not. They also use text mining and web mining tools. Thus an organization may perform customer behavior analysis, get personalized recommendations, discover market trends, perform what-if strategic analysis, process temporal queries, and perform temporal reasoning (against structured part of knowledge).

Level 4 (Temporal): an organization is mature in terms of Big Data and temporal knowledge usage. Thus it uses Big Data, e.g. social data and also structured and unstructured temporal knowledge. It implements the following IT solutions: Big Data analytical tools, temporal knowledge bases, other artificial intelligence systems (such as multi-agent systems collecting social data) and others. The following functionalities are available: text and opinion mining, sentiment analysis, resource optimization, discovery of customer usage patterns, holistic analysis of clients, qualitative and quantitative temporal reasoning, possibility analysis, belief representation and analysis.

The BDTMM model presented in this paper is of a descriptive nature because it may be used to assess the maturity level of an organization. This functionality makes the model differ from e.g. Bill Schmarzo's proposal (see [Schmarzo 2013]), because his Big Data Maturity Index is a transitive model, enumerating steps and activities to be followed and performed by an organization to reach a given maturity level.

The next important feature of the BDTMM model is that it allows to flawlessly and coherently integrate BI solutions with Big Data ones, because the model takes into consideration different ICT options and functionalities.

3. Assessing maturity level, or preparedness to use Big Data

Even if an organization is equipped with a tool that may serve as a guide in implementing successive solutions concerning ICT, data/knowledge, and organizational issues that may lead to making use of Big Data in a mature way, it may however be difficult to assess on which maturity level the organization currently is.

For this reason many of the maturity models are delivered with so-called self-assessment tools aimed at helping an interested organization in determining its maturity in certain domain, such as Business Intelligence systems or Big Data analyses. For example, self-assessment forms and questionnaires are added to the following maturity models:

- for BI: Gartner's model, TDWI model, Enterprise Business Intelligence Maturity (EBIM),
- for Big Data: TDWI model.

Also the maturity model presented in this paper in the previous section is accompanied by a specialized self-assessment tool. This is a form prepared by the author of this paper, and based on the 7-point Likert scale, with questions and propositions stemming directly from the BDTMM model. We have decided to use the broader, 7-point scale instead of the commonly used 5-point one due to the complexity of the domain being assessed.

The form is presented below.

Assessment form of an organization's preparedness to adopt Big Data

Please read carefully the characteristics concerning different IT solutions and functionalities. Think of a real situation in your organization concerning these solutions. Please mark the results using the scale 1-7, choosing the number according to the real situation, the dominant tendencies in your organization. Your opinion should be expressed using one of the following values: 1 – I strongly disagree with the statement, 2 – disagree, 3 – weakly disagree, 4 – neither agree nor disagree, 5 – weakly agree, 6 – agree, 7 – strongly agree.

Our organization	Little (Level 0-1)		Medium (Level 2-3)			Much (Level 4)	
	Strongly disagree	Disagree	Weakly disagree	Neither agree nor disagree	Weakly agree	Agree	Strongly agree
1	2	3	4	5	6	7	8
I. Data/knowledge. Our organization makes use of:							
1. Static knowledge (e.g. knowledge in DW)	1	2	3	4	5	6	7
2. Multidimensional data (e.g. data in DW)	1	2	3	4	5	6	7
3. Sequential knowledge (e.g. sequences of events in DW)	1	2	3	4	5	6	7
4. Unstructured data sources	1	2	3	4	5	6	7
5. Time-stamped sequences (e.g. time series)	1	2	3	4	5	6	7
6. Time-stamped knowledge (e.g. knowledge on DW evolution)	1	2	3	4	5	6	7

1	2	3	4	5	6	7	8
7. Sensor data, click stream data	1	2	3	4	5	6	7
8. Unstructured knowledge (e.g. knowledge from web)	1	2	3	4	5	6	7
9. Structured temporal knowledge (e.g. rules with time component)	1	2	3	4	5	6	7
10. Social networking data	1	2	3	4	5	6	7
11. Unstructured temporal knowledge (e.g. commonsense knowledge with time component)	1	2	3	4	5	6	7
II. IT solutions – our organization implements:							
1. Data warehouse	1	2	3	4	5	6	7
2. Business Intelligence	1	2	3	4	5	6	7
3. Knowledge base system (e.g. expert system)	1	2	3	4	5	6	7
4. Intelligent dashboards	1	2	3	4	5	6	7
5. Sequential knowledge base systems (e.g. expert systems with sequences as: If product_success BEFORE demand_raise Then supply_raise)	1	2	3	4	5	6	7
6. Business optimization software	1	2	3	4	5	6	7
7. Time-stamped knowledge base systems (e.g. expert systems with time series)	1	2	3	4	5	6	7
8. Data mining tools	1	2	3	4	5	6	7
9. Hadoop/other	1	2	3	4	5	6	7
10. Temporal knowledge base (knowledge on time-dependent phenomena, e.g. changes in demand)	1	2	3	4	5	6	7
11. Big data analytics software	1	2	3	4	5	6	7
12. Temporal knowledge base system (e.g. expert	1	2	3	4	5	6	7

1	2	3	4	5	6	7	8
system with temporal knowledge on varying prices of shares, and situation-dependent investment rules)							
13. Other AI solutions	1	2	3	4	5	6	7
III. Functionalities – our organization performs:							
1. Static decision support (e.g. using expert system or BI system)	1	2	3	4	5	6	7
2. BI multidimensional analytics/reporting	1	2	3	4	5	6	7
3. Predictive analytics/ advanced statistics	1	2	3	4	5	6	7
4. Basic data mining on structured data (e.g. in DW)	1	2	3	4	5	6	7
5. Advanced analytics	1	2	3	4	5	6	7
6. Advanced data mining	1	2	3	4	5	6	7
7. Temporally extended static rules (e.g. If payment_date = t_1 and job_loss = t_2 and $t_2 < t_1$ then credit_at_risk)	1	2	3	4	5	6	7
8. Structured big data analytics	1	2	3	4	5	6	7
9. Partly temporal reasoning (e.g. time-series analysis)	1	2	3	4	5	6	7
10. Unstructured big data analytics	1	2	3	4	5	6	7
11. Temporal reasoning (e.g. reasoning with situation- and time-dependent investment rules in expert system, resulting in investment strategy)	1	2	3	4	5	6	7

Source: own elaboration.

The form (questionnaire) structured as above allows an organization to assess at which level of maturity in the context of using Big Data it currently is. In other words, how well prepared the organization is to fully make profits from Big Data analyses. This is so because the answers in the form are linked with the maturity levels of the proposed maturity model. This solution differs from e.g. TDWI's self-assessment tool because it is formalized and contains a point scale, while TDWI's form is a questionnaire containing both open-ended and closed-ended questions concerning IT solutions in an organization, thus the person using the TDWI's assessment tool has to assess the firm's maturity on his/her own.

4. Conclusions and future research

In the paper a new maturity model concerning an organization's preparedness to adopt Big Data has been presented together with a self-assessment tool, also elaborated by the author. The tool is based on the well-known Likert's scale. In our opinion a maturity model that is not followed with a tool allowing an organization to assess its maturity level is incomplete and thus difficult to use in management practice. This observation was the starting point in the process of preparing the above presented assessment form, which allows the decision makers to assess the Big Data maturity level of their organization.

The above proposed model is a temporal one because it is built on the basis of the time dimension, as in our opinion this is the most important feature and dimension of the data called "Big". The already existing models mentioned in the paper do not address the temporal characteristics of Big Data.

The next step in the research concerning our maturity model and the assessment form is the verification of both tools in selected organizations. Such a verification is the next planned research stage.

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